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13. ABSTRACT *(Maximum 200 words)*

A holographic optical system listens to an incoming signal and extracts the most common repetitive temporal features of that signal. An example might be to extract the features of Morse code, which consists of two tone lengths and two pause lengths. This optical system is self-organizing, in that very little *a priori* information is imbedded in the system to indicate what form the temporal signals take. The primary constraints imposed on the signal is 1) finite bandwidth 2) limited feature duration and 3) rates of reoccurrence. The optical apparatus uses a photorefractively pumped multimode optical oscillator having a delay line in the feedback loop. The delay line serves to translate the temporal dimension into a spatial one, and it also builds into the system a notion of the direction of time. Temporal feature extraction takes place as a competitive interaction among sets of modes, which are termed chronomodes. Experiments illustrate the principles of such a system by extracting the two most probable temporal features from a signal imposed on a laser beam.

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Temporal Feature Extraction in Photorefractive Resonators

Final Report

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1. Introduction

This report describes the last phase of our work under grant DAAL03-91-G-0312. In this phase we have applied some of the concepts and devices developed earlier to the construction of a novel optical processor. The system described here extracts by its own meaningful temporal features from its input environment.

A temporal feature extractor detects the main characterizing temporal features within a more or less structured signal. The task it accomplishes is better understood by using a simple example. Imagine to tune across a short-wave radio band. It will be easy to recognize a channel that carries Morse code; even without knowing the code. That is because Morse code consists of a simple set of temporal features (a dot, a dash and two pause lengths), and a Morse signal is characterized by their repeated occurrences. It does not take very long for the brain to identify the features as the dominant content of the received signal. The task of our feature extractor is just this: to discover on its own the dominant features in a temporal signal characterized by repetitive entities [1, 2]. This task is a precursor to the more complex processing required for the self-organized feature extraction and recognition of audio and sonar signals.

In a previous project phase we did implement an optical classifier for the recognition of acoustic signals [3] which was based on a time-delay neural network architecture [4]. This system required the presence of a teaching signal. Unlike the acoustic processor, the present temporal extractor is self-organizing [5-7] and does not need a teacher. This approach is most helpful when, like in the currently studied problem, one does not have a priori knowledge of what or when to learn from the input environment.

2. Highlights

A model for temporal feature extraction is discussed and its optical hardware implementation is described in detail. The extraction of features within both binary and analog temporal signals modulated on a Gaussian beam are demonstrated. The separation of two different temporal signals into different output ports through the competitive dynamics in the optical resonator system is also successfully verified.

3. Basic Principles of the Optical System

The extraction of temporal features can be achieved using the optical architecture, which basic scheme is shown in Fig.1. The system contains two basic processing elements, the gain crystal (long-term memory) and the optical delay-line [8] which provides a short-term memory element. The system operation makes use of the time-domain cooperative interactions provided by the delay line in addition to the nonlinear photorefractive dynamics in optical resonators [9].

In Fig.1 each ring corresponds to a spatial mode in the optical resonator. The group of modes share a photorefractive gain crystal and are arranged along the delay coordinates of the optical delay line. At each moment in time, the delay line temporarily stores the optical field of each mode (e.g., mode j), and later injects the stored field into the neighbor mode (j+1). Its action can be expressed as

$$E_{j+1}(t) = G_{j+1}S(t) + \mu E_j(t-\tau), \qquad (j=1, \ldots, n\text{-}1) \tag{1}$$

where $E_j(t)$ is the optical field within mode j at time t, G_j is a normalized grating component in the gain crystal, and $0<\mu<1$ is a numerical factor characterizing the decay along the delay line. The temporal signal $S(t)$ is imposed on a Gaussian pump beam as modulation on its amplitude and/or phase; this serves as input to the system. The grating G_j in the gain crystal scatter the pump beam into the j^{th} resonator mode; this part of the light contains information about the present input. In addition, each mode receives injected light from the delay line which contains information about past input signals. Note that for clarity of presentation a spatially discrete array of n modes with time delay τ between two neighboring modes has been assumed. However, this is not necessarily the case; the modes can also be continuously distributed in space, as in the experiments described later. Using Eq.(1), the total optical field $E_j(t)$ in the j^{th} mode at time t can be written as

$$E_j(t) = \sum_{k=1}^{j} G_k S(t - j\tau + k\tau)\mu^{j-k}, \qquad (j=1, \ldots, n). \tag{2}$$

From Eq.(2) it is clear that given a set of gratings, the optical field in a mode is an inner product between the gratings (in space) and the input signal (in time). Thus, the gratings can be thought of as defining a temporal feature for the system. In general, the maximum time delay determines the length of temporal features that the resonator can be sensitive to, and the bandwidth of the optical delay line defines the minimum time-scale for input signal changes.

The photorefractive grating G in the gain crystal starts initially from noise. It grows when oscillations in the resonator begin to build up. The above unidirectional coupling in the delay element (Eq. (1)) modifies the spatial structure of the collection of all the coupled modes. We refer to this mode collection as a chronomode. The final equilibrium structure and the equilibrium grating ($G_1 \ldots G_n$) are determined by the temporal characteristics of the input signal $S(t)$ of interest. In other words, the gain crystal grating matches the particular chronomode spatial structure corresponding to the dominant temporal features. The grating can be thought of as a matched filter, in the sense that it permits resonator oscillation only when the dominant feature is present at the input. For non-dominant features, that is features occurring only rarely, oscillation is inhibited.

Fig.1 shows a single group of modes, that is a single chronomode. The system can contain multiple chronomodes, each arranged along a different delay line. If the chronomodes share a common gain crystal, each of them can learn a particular temporal feature of the input environment. Fig.2 shows schematically two chronomodes competing in the central gain crystal. Each resonator ring in Fig.2 is expected to respond strongly when its learned feature is presented at the input.

We should note that the simple optical schemes described above can be translated in equivalent neural network architectures including time delays within sets of output units. Our analysis of the network models, of which we skip details here, has proven very helpful to qualitatively predict the general behavior of the actual architectures under consideration.

4. Hardware Implementation and Experimental Verification

We first describe the set-up shown in Fig. 3 used to implement the self-organizing temporal feature extractor. All the beams shown are from a single frequency, cw Ar-ion laser ($\lambda = 514$ nm), and are p-polarized. The system consists of an optical resonator formed between the rotating photorefractive delay line crystal ($BaTiO_3$ #1) [8] and the feedback mirror M_1. The resonator is pumped by a modulated Gaussian beam entering the gain crystal (45^o-cut $BaTiO_3$, #3) which lies in the image plane of crystal #1. Note that the photorefractive delay line works in the phase-conjugate configuration, the counter-propagating pump beam is generated by a phase conjugate mirror implemented by four-wave mixing in the crystal $BaTiO_3$ #2.

Each mode in the resonator finishes a round trip by tracing the same path twice, and reflecting twice at crystal #1. The optical phase is reproduced after one round trip, therefore the resonance condition is maintained independent of the optical length of the beam path. The time delay coordinate of the delay line is along a cone [8], a short portion of it essentially lie along the direction perpendicular to the plane of Fig. 3. A group of modes distributed along this vertical direction defines a chronomode in the experiment. Its transverse profile is constrained by a pair of slot apertures in the horizontal plane. Fig.3 shows two chronomodes identified by the differently dashed lines. In general the system can have many chronomodes as long as there is sufficient gain in the pump crystal (#3) so that all can be above threshold and oscillate. The vertical length of the slot apertures defines the angular range over which modes enter the delay line and gain crystals, which effectively defines the maximum time delay within the system.

Note that the scheme of Fig.3 is not unique. Other architectures have been successfully tested. All of them share the common characteristics of containing a long term memory gain crystal and a short term memory rotating crystal within differently designed photorefractive resonators. The scheme of Fig.3 was found to be the most robust because amplification occurs in the gain crystal for light traveling in both directions along the resonator path. This decreases the oscillation threshold.

We have performed experiments to verify the operation of the signal processor using binary, analog as well as partially noisy signals. We could verify that the following two properties are satisfied:

(1) If a certain temporal feature is clearly dominant, a system containing a single chronomode will select that feature at the expense of all other non-dominant ones.

(2) In a system with two competing chronomodes, each of two equally dominant features is associated with one of the chronomodes. If there is only one chronomode an ambiguous state may result.

In the experiments a dominant feature (sub-signal) is the one which is presented most often within the input signal. By changing the rate of occurrence of a selected sub-signal the input can be deliberately biased in any wanted direction. We present below the results of two experiments which demonstrate the two above properties. Deep experimental details are skipped, they can be found in the enclosed preprint of Ref. [1].

Fig.4 shows the results of an experiment demonstrating property (1), the learning of the most-frequently presented sub-signal within a single-chronomode system. The phase-modulated binary signals defined in the caption are used. Note that by switching from + to - the pump beam gets opposite phase but keeps the same intensity. In Fig.4 the total intensity of the resonator is plotted as a function of time as different sub-signals are applied at the input. The figure shows the equilibrium state which is reached after about 20 learning cycles. In the experiment of Fig.4a sub-signal S_1 dominates S_2 by a ratio of 2 to 1. As expected, in this case the resonator response is much stronger while S_1 is applied. In the opposite case (Fig.4b) S_2 dominates by 2 to 1 and the chronomode responds now to S_2. Note that, as a sub-signal is presented at the input, the resonator response grows continually from the beginning till the end. This is an interesting property of the self-organized state. The system can be thought of as being able to accumulate evidence continually over time, which is somewhat similar to the human ability to continually anticipate and make predictions as we listen to, e.g., speech or music. Other types of signal processors such as time-delay neural network [3, 4] do not posses this property.

Next we demonstrate property (2). In this experiment the resonator contains two pairs of apertures and thus two chronomodes can oscillate. This situation corresponds to the scheme of Fig. 2. Analog sub-signals with strong random components overlapping regular sinusoidal functions are used. The form of the two sub-signals (Signal 1 and Signal 2) to be learned is shown in Fig.5(a). Fig. 5(b+c) show the response of the two chronomodes in the equilibrium state. Each image corresponds to the resonator intensity profile at the moment when a signal has just been applied at the input. The pictures are taken at the place of the detector in Fig. 3 using a CCD camera. One sees that one of the chronomodes responds strongly to Signal 1 and the other to Signal 2. Each chronomode has learned to associate with a particular sub-signal. Note that in this experiment the basis for the recognition is given by the highly autocorrelated sinusoidal functions underlying the two signals. Completely noisy and unstructured signals cannot be learned.

We have studied different expansion schemes for the system of Fig.3. In order to use temporally and spatially modulated signals at the system input the electro-optic modulator has been replaced by a nematic liquid crystal spatial light modulator (SLM) taken from a TV projector. It was possible to get oscillation in the resonator when a short video movie was played at the input. However, only poor discrimination among similar movies could be achieved. The reason for that was the difficulty to obtain zero-mean input signals using the available SLM's. Non zero-mean signals tend to be characterized by their large zero order component. By choosing a proper configuration we were successful in constructing zero-mean signals using conventional SLM's, however at the costs of an unaffordable waste of light. In contrast, spatially and temporal modulated zero-mean signals with large light intensity can be easily obtained when a discrete small number of independently time-modulated Gaussian beams are used instead of a SLM. Excellent signal discrimination could be obtained using two such beams for pumping a system similar to the one in Fig.3. This approach is relevant for potential system expansions through resonator cascading.

5. Conclusions

In the final phase of the present research project we have developed a self-organizing optical processor which can extract meaningful temporal features from its input. The system makes use of the delay-line device developed earlier [8]. Like the previously investigated network for acoustic signal recognition [3], also the present system functions through the interaction of short- and long-term memories. However, the imbedding of the two elements in a photorefractive resonator makes the current system suitable for unsupervised learning. We have experimentally demonstrated the extraction of both binary and analog features, as well as the separation of two features into different outputs.

In a Morse signal the letters of the alphabet are comprised of a short sequence of basic Morse features; words are comprised of a sequence of letters, and so on. Similarly, complex temporal signals such as speech or music are characterized by a given hierarchy of short and long temporal features, where longer features are comprised of the basic (short) ones. In this work we have developed a processor which detects the most basic features. The unsupervised identification of complex signals should be possible using a cascaded configuration of many such processors.

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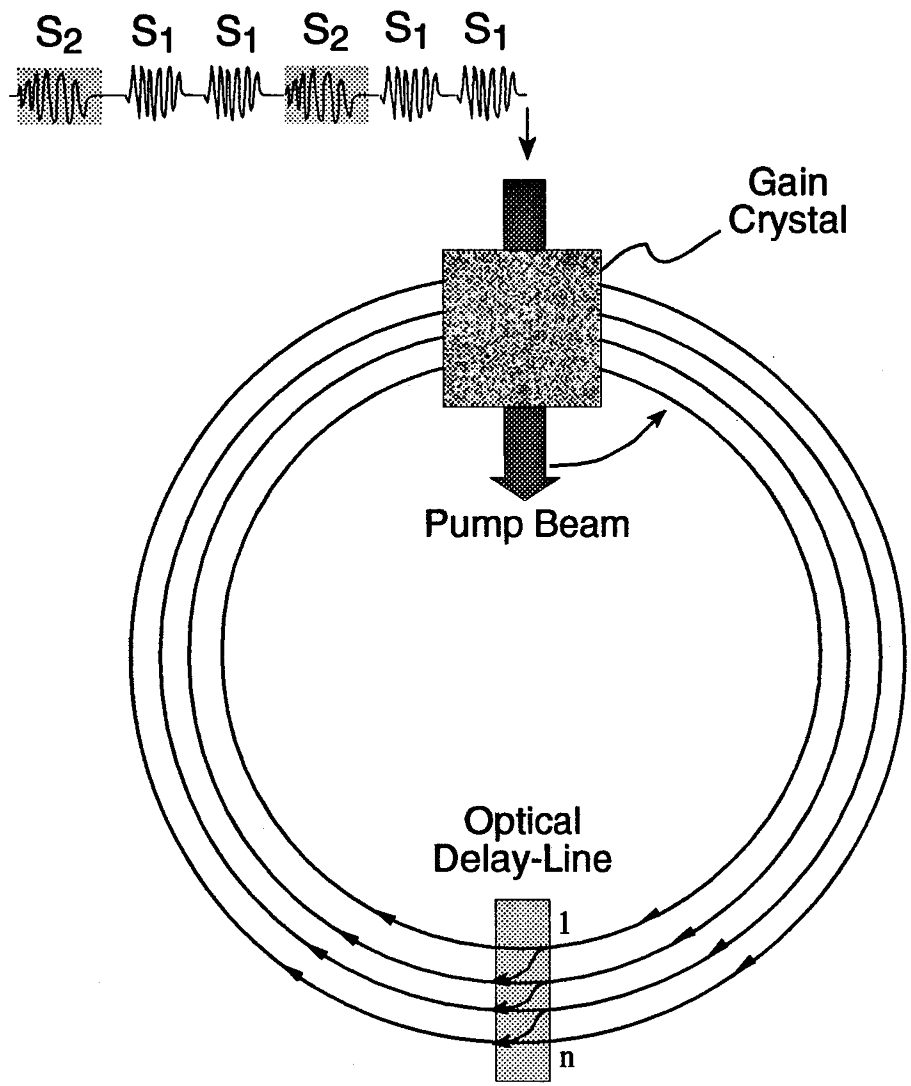

Fig. 1: Schematic of an optical resonator incorporating a delay line for learning temporal information. The collection of coupled rings forms a chronomode.

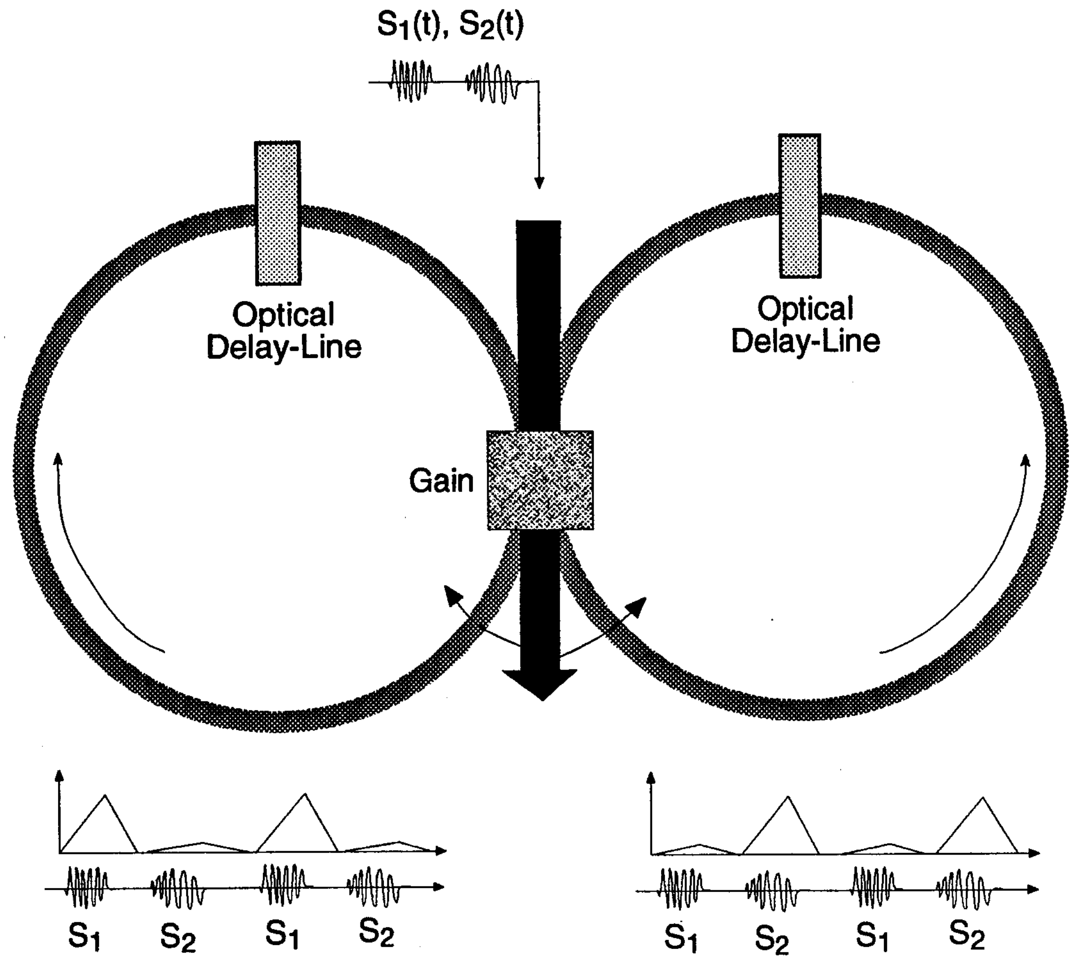

Fig.2: Schematic of two competing resonators. Each resonator ring learns to be associated with one of the temporal features. The corresponding chronomode responds only when that feature is present at the input (lower plots).

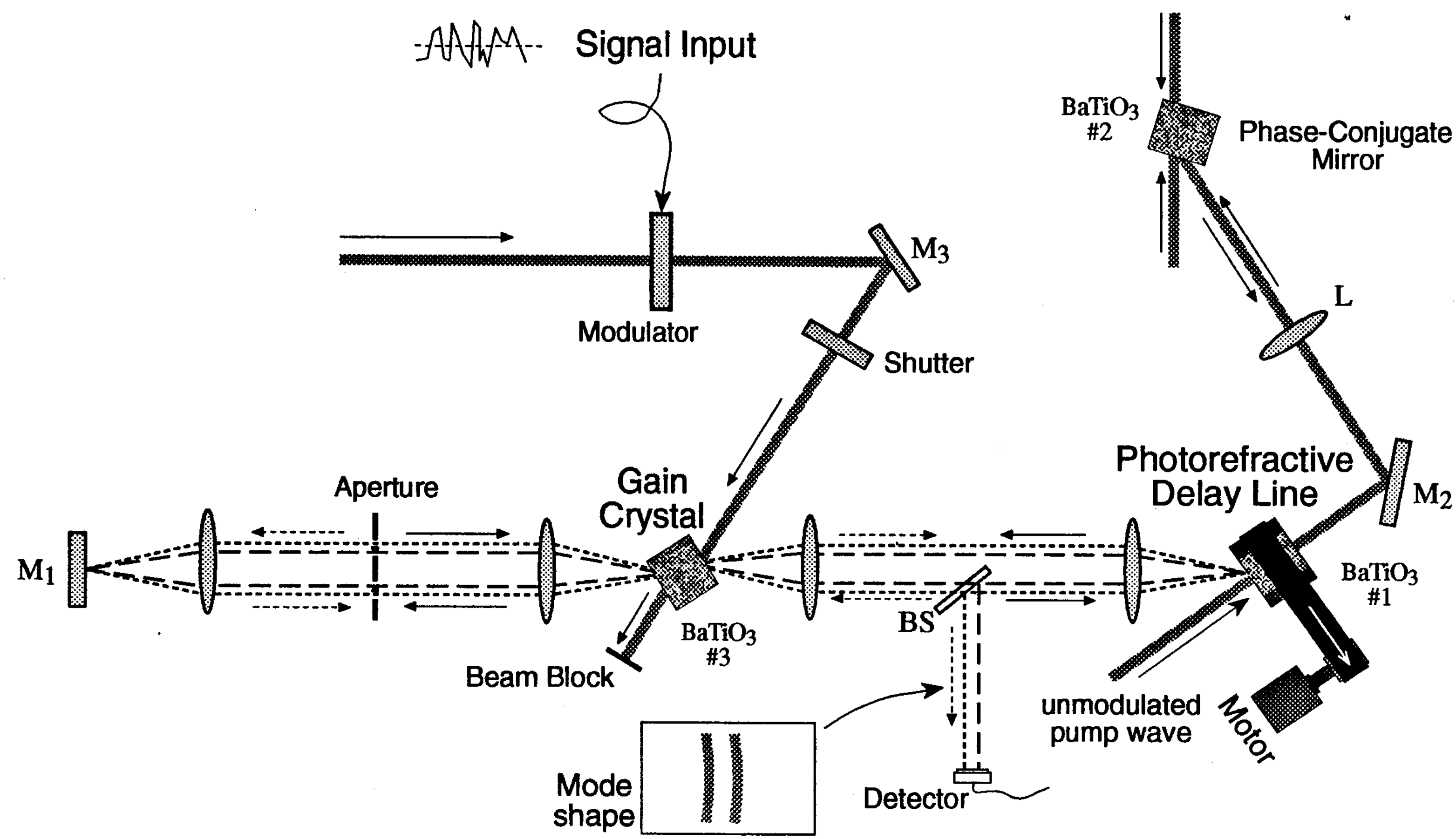

Fig. 3: Experimental Set-up. Resonator oscillation is between mirror M1 and the rotating crystal BaTiO3 #1. Two chronomodes are identified by the dashed and dotted lines.

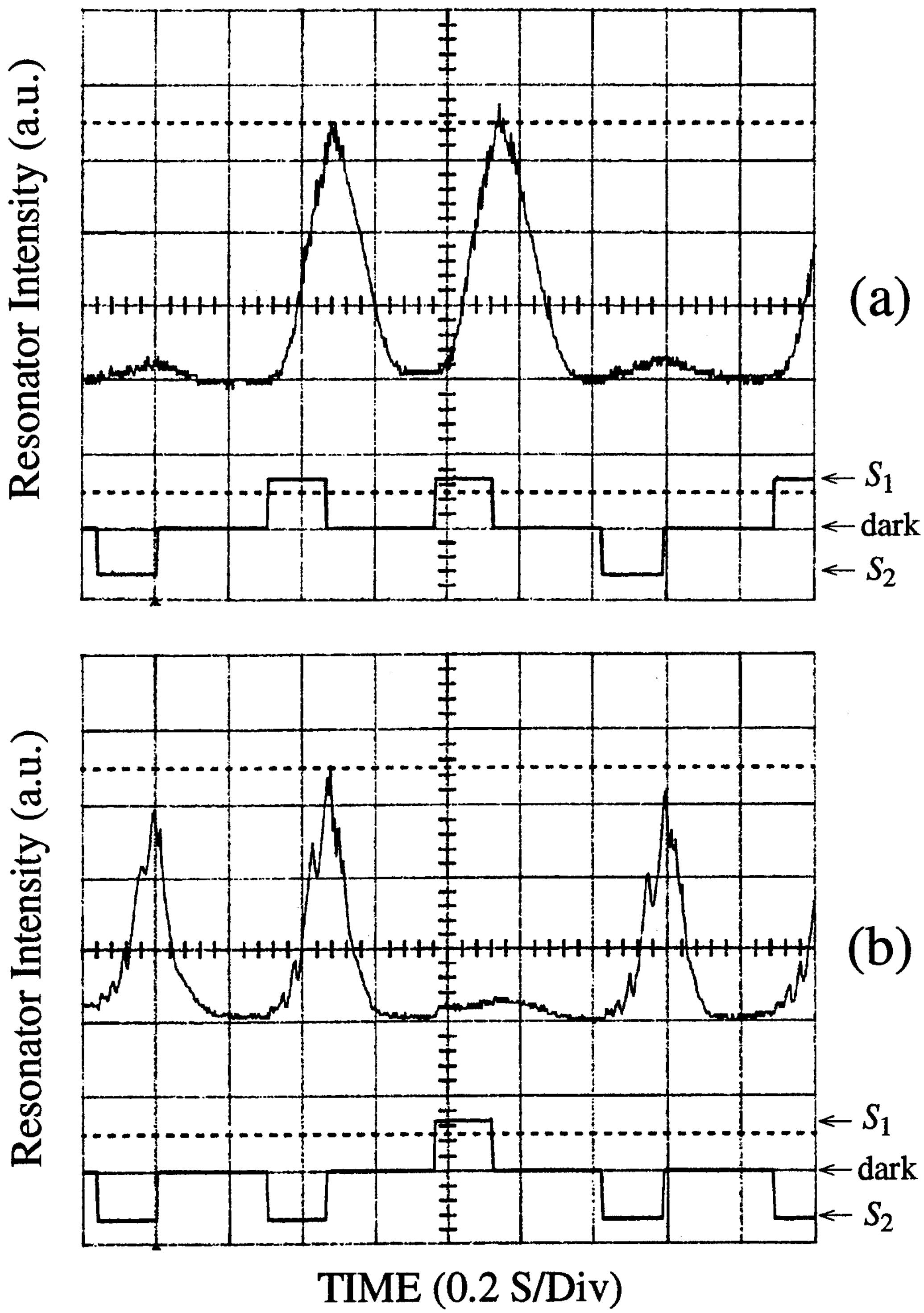

Fig. 4: Steady state resonator response after presentation with two binary sub-signals S1 and S2. S1=(+-+-+-+-+-+-+-+-), S2=(+-++---+++++----). a) S1 dominant, it occurs twice more often than S2, the resonator learns S1. b) S2 is dominant, the resonator learns S2. The lower traces indicate which sub-signal is present at the input at a given time. The 16 bit sequences begin at the left edges and end at the right edges of the square pulses.

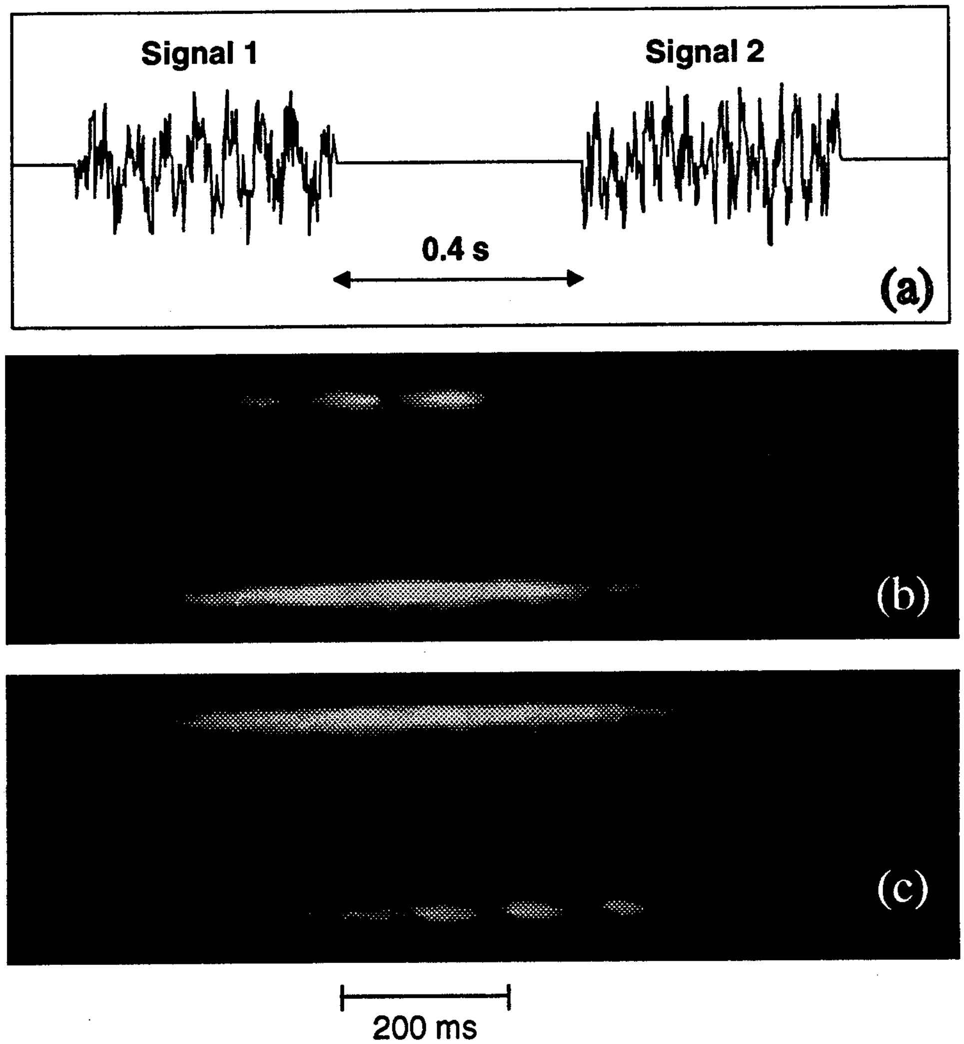

Fig. 5: Self-organized separation of two analog temporal sub-signals into two chronomodes. (a) Modulation of the input signals 1 and 2. The two signals are presented alternately. (b) Istantaneous profile of the two chronomodes in response to Signal 1. (c) Same in response to Signal 2. The lower chronomode has learned to be associated with Signal 1, the upper with Signal 2.